Edge Computing for Cattle Behavior Analysis

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***Abstract*—Smartphones, particularly iPhone, can be relevant instruments for researchers because they are widely used around the world in multiple domains of applications such as animal behavior. iPhone are readily available on the market, contain many sensors and require no hardware development. They are equipped with high performance inertial measurement units (IMU) and absolute positioning systems analyzing user's movements, but they can easily be diverted to analyze likewise the behaviors of domestic animals such as cattle. Using smartphones to study animal behavior requires the improvement of the autonomy to allow the acquisition of many variables at a high frequency over long periods of time on a large number of individuals for their further processing through various models and decision-making tools. Indeed, storing, treating data at the iPhone level with an optimal consumption of energy to maximize battery life was achieved by using edge computing on the iPhone. This processing reduced the size of the raw data by 42% on average by eliminating redundancies. The decrease in sampling frequency, the selection of the most important variables and postponing calculations to the cloud allowed also an increase in battery life by reducing of amount of data to transmit. In all these use cases, the lambda architectures were used to ingest streaming time series data from the Internet of Things. Cattle, farm animals' behavior consumes relevant data from Inertial Measurement Unit (IMU) transmitted or locally stored on the device. Data are discharged offline and then ingested by batch processing of the Lambda Architecture.**

***Index Terms*—cattle behavior analysis, edge computing, farm' animal, iPhone, Flutter**

I. Introduction

Classifying animal behavior requires to measure its movements and displacements. But, often the best parameters to sample and their frequency to accurately identify a behavior is unknown before adequate models are developed. Hence, researchers want to be able to measure a large quantity of high-frequency parameters in order to not miss out any valuable information. Moreover, researchers do not have the time to develop tailor-made sensors to measure these different parameters. The iPhone provides a simple way to quickly measure a multitude of settings at an affordable price.

iPhone are widely widespread around the world and are equipped with several sensors such as a location and global positioning system (GPS), an inertial measurement unit (IMU) from which signals are easily extractable for the user, saving long hardware developments. Sensor Data is such an application available on Apple Store allowing to acquire 41 parameters up to 100 Hz rate. Recorded signals come from the IMU that contains a 3-axis accelerometer, a 3-axis gyroscope and a magnetometer (digital triaxial compass). The accelerometer is used to measure inertial acceleration. The gyroscope measures angular rotation. The magnetometer improves the precision of the gyroscopic measurements by correcting the yaw drift using the magnetic pole [1].

For such reasons, iPhone are used in various applications from different domains such as human posture and movement for upper arm, as in [2], human body position, as in [3], sports monitoring, as in [4] [5] and cattle behavior monitoring, as in [6].

In the latter, the IMU data were collected during specific movements. These data were related to the filmed behaviors of the animals which aim to identify the parameters that make it possible to identify animal's behavior and their variation amplitude. When large amount of data must be processed, it can be collected and processed in an architecture as proposed in [1] [7] [8] allowing the collection and the sharing of data from all over the world in order to develop global behavioral models.

To help scientists specialized in animal behavior in using simple devices as iPhone in their research instead of alternative tailored-made measuring devices, we assessed the reproductibility of the measurements with different models of phones. We also checked the impact of data sampling rate as

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well as the amount of data that collected according to the iOS version on battery life.

II. Background

In a previous paper, we have developed a methodology to acquire data by means of refurbished iPhone 4s to acquire behavioral data with Inertial Movement Unit (IMU). The approach was published in Adriamandrosco et al., 2017 [6].

Afterwards, we have progressively developed our cloud architecture through different use cases such as the health of bee hives [9], connected pivot-center irrigation [10], landslides monitoring [11] [12], digital phenotyping [13] [14], bird nesting [15], AI-IoT [16], smart poultry [17], smart home [18], smart building [19], smart city [20], smart campus [21], urban agriculture [22] [23] and patients and Elderly Monitoring [24]. In all these use cases, lambda architectures were used to ingest streaming time series data from the Internet of Things. Cattle, farm animals' behavior and the health of bee hives behavior process usefull data from Inertial Measurement Unit (IMU) which are transmitted by using the LoRaWan protocol. On the other hand, these data can be locally stored on the device in a first stage, and then discharged offline and ingested by batch processing of the Lambda Architecture in a second stage.

This architecture was adapted to collect, process and store the data stored on iPhone 4s and 5s for cattle behavior [1], and farm animals' behavior [7].

In this paper, we propose an improvement and a generalization of animal data acquisition process and the analysis of collected data. So, we compare a newly developed open source application supporting Android and iOS with the old approach using a proprietary system. This new application allows to log more sensors than IMU data and associate each sensors with meta data to facilitate the curating of data thereafter. Then, we have developed an online service to analyze files logged with old iPhone and the new application and tag video of the animal behavior. Tagged video and logged data are synchronized in order to extract the variation parameters associated to each type of macro and micro behavior.

III. Material

iPhone 4s and 5s are compared with the latest version supported of iOS on each device (see Table I). On each iPhone version sensor Data release 1.26 is installed and iOS version has been updated to the last release. Table II presents parameters logged by Sensor Data. All other applications are removed to eliminate interferences in the measurement of the battery life.

IV. Data collection

The precision of both iPhone was evaluated by attaching an iPhone 4s with an iPhone 5s using elastics. The two-solidarized iPhone were placed on an animal in order to compare possible variations in the IMU measurements. The accuracy of the accelerometer, gyroscope and location sensor was evaluated with a displacements table and a checker. These instruments allow respectively mastered movements and 3D - acceleration and 3D - rotation.

TABLE I
Configuration of iPhone 4s and 5s

iPhone	Configuration	
	iOS	Inertial Measurement Unit
4s	8.3	STMicro 8134 33DH 00D35: 3D axis accelerometer; STMicro AGD8 2135 LUSDI: 3 axis gyroscope
5s	10.3	Bosch Sensortech BMA220: 3 axis accelerometer; STM B329: 3 axis gyroscope; AKM AK8963 compass 3 axis

The autonomy of the battery of new iPhone 4s and 5s is evaluated at different sampling frequency: 1, 2, 3, 5, 10, 20, 30, 50, 100 Hz with all the 41 parameters and replicate 5 times. The lowest frequencies (1 to 5 Hz) should cover most kinds of movements imprinted by an animal. The frequencies 10, 20, 30 and 50 Hz are a tenfold increase in previous sampling rates allowing a good representation of phenomenon as used in most animal behavior applications. Although, in theory according Shannon/Nyquist the double of the frequency of the studied phenomenon should be enough. Finally, 100 Hz frequency is the maximum rate supported by the device. In a second time, the same measurements were done with measured parameters only and replicated 3 times. The replication of the measurements allowed to evaluate standard deviation.

Table II shows data acquirable and calculable with Sensor Data on iPhone based on the accelerometer, gyroscope, magnetometer, location and proximity sensors. Only acceleration on x,y,z [g], Euler angles (pitch, roll, yaw), magnetic data, magnetic and true heading, latitude [°], longitude [°], altitude [m] are real measured data. All the other parameters are calculated from the previous ones.

TABLE II
Parameters acquired

Sensor	Parameter	Unit
Accelerometer	Acceleration on x, y, z	g
Gyroscope	Euler angles (pitch, roll, yaw)	rad
	Attitude quaternion on x, y, z	rad
	Rotation matrix (3x3)	-
	Gravitational component of acceleration	g
	User component of acceleration	g
	Rotation rate	rad.s-1
Magnetometer	Magnetic data	µTesla
	Magnetic and true heading	°
Location	Latitude and longitude	°
	Altitude and accuracies	m
	Course	°
	Speed	m.s-1
Proximity Sensor	Proximity	[0,1]

V. Data compression

An application programmed with Dart language by using Flutter Google UI toolkit was developed to measure the compressibility of data by reducing the precision. In this use case, all data must be preserved in order to allow future exploitation

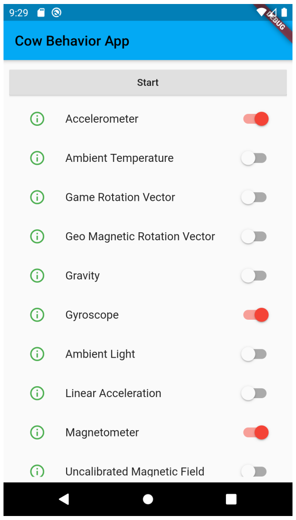


Fig. 1. Sensor Choice

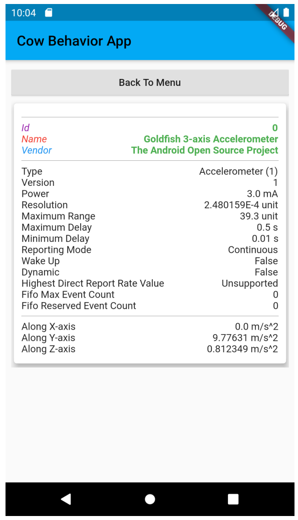


Fig. 2. Meta Data of sensor

of them. All raw data are logged with a decimal precision of 6 digits. The compression of raw data by eliminating redundancies has been done. The level of compression has also been evaluated on truncate data to 3, 4 and 5 decimal digits.

Flutter framework was chosen because it offers the possibility to natively compile applications for Android and iOS platform. The developed application namely 'Cow Behavior App' integrates logging activity at a chosen frequency like Sensor Data. Cow Behavior App allows also users to choose sensors among those available on the device and log their data on the SD Card for Android, in internal memory for iOS and log a wide panel of other data than IMU (See Fig. 1). Each sensor is associated with its own meta data gathered in a single file which is exported in JSON-LD format (See Fig. 2). Meta data describes properties of the sensor such as the name, the model, the manufacturer, limits of rate acquisition, and sensor accuracy.

VI. Data Analytics

We have also developed an Online Analysis Service freely available on https://www.cowbehavior.cloud. This Service allows to analyze CSV Files collected by means of iPhone, uploads them in the cloud architecture, and determines cow behavior by application of the algorithm and coefficients proposed in Andrianmandroso et al. 2017 [6]. Registered Users on the website, can also access to a more performant and tweakable version. This version which is dedicated to registered users contains also a set of specific tools used to tag behaviors on video. Annotated videos are then synchronized with data acquired with sensors of cellphones to extract parameters range of variation associated of each tagged behavior.

At the end of the analysis, this service according to user choices can produce a detailed report, export results in different data file formats such as Excel File (.xlsx), OpenDocument Spreadsheet (.ods), Comma-Separated Values (.csv), cartographic file format such as Esri Shapefile (.shp), Google Earth (.kmz). The Fig. 3 shows an example of some results obtained at the end of the treatment of the file alldata.csv.

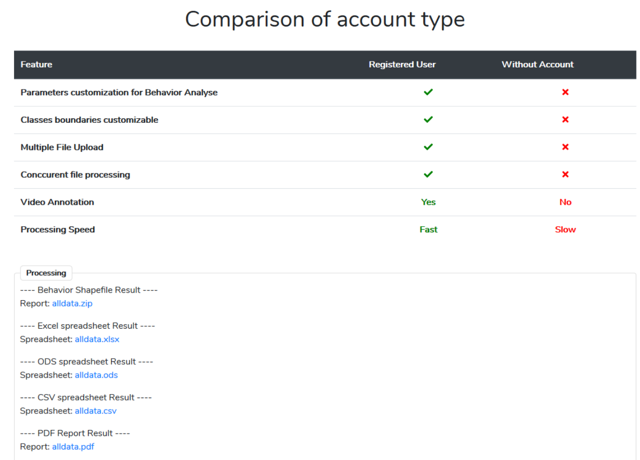


Fig. 3. Online service processing

VII. Results

Both iPhone 4s and 5s solidarized and placed on animal gave similar results in terms of accelerometric, gyroscopic and magnetic measurements. These measurements were confirmed by imposing controlled movements and vibrations on both iPhone. The both iPhone measured correctly controlled movements with a precision of 10^{-3}. As shown on Table III, the compression of data achieves an average raw data size reduction of 43.5% by eliminating redundancies. The truncation of raw data respectively to 5, 4 and 3 digits and the elimination of redundancies reduces up to 44.5% on average the size of data to store. The small decrease on average of the size of data with 6, 5, 4 and decimals can be explained by the combination of parameters inside groups that limit the possibilities of compression.

The evolution of the compression rate is not significant for groups of data by opposition to individual data. Compressibility for individual parameters is very variable because it depends on one hand of the precision of sensors that are contained in the IMU, and on the other hand of the activity of the animal. Furthermore, the acquisition rates of sensors are different and therefore the variability in data. Table IV, shows the mean autonomy time of batteries for two models of iPhone obtained with different sampling frequency for 15 and 41 parameters, respectively. The 15 parameters are those actually measured by the IMU. The 41 parameters are measured and calculated on the basis of the 15 measured parameters.

Table III and Figure 4 shows that the iPhone 5s has a battery life 50% longer on average compared to the iPhone 4s. The improvement in autonomy can notably be explained by the presence of a better co-processor in the iPhone 5s. Otherwise, Table IV does not show significant changes whether for 41 or 15 parameters.

TABLE III
COMPRESSION RATE OBTAIN BY TRUNCATURE OF DATA

Data Group	Mean Compression rate [%] by group			
	6 decimals	5 decimals	4 decimals	3 decimals
Acceleration (X,Y,Z)	4.26	4.26	4.26	4.27
Euler angles of the device (Roll,Pitch,Yaw)	24.13	24.13	24.13	24.13
Attitude quaternion (X,Y,Z,W)	24.13	24.13	24.13	24.47
Rotation matrix	24.13	24.13	24.13	24.15
3D Gravitational acceleration (X,Y,Z)	24.13	24.13	24.23	32.02
3D User acceleration (X,Y,Z)	24,13	24,13	24,13	24,25
Rotation rate (X,Y,Z)	24.13	24.13	24.13	24.13
Magnetic Heading, True Heading, Heading Accuracy	0.01	0.01	0.01	0.01
Magnetometer data (X,Y,Z)	60.82	60.83	60.84	60.86
Latitude, Longitude, Position Accuracy	99.85	99.94	99.99	100.00
Course, Speed	99.75	99.75	99.75	99.75
Altitude	99.99	99.99	99.99	99.99

Table IV shows the mean autonomy time of batteries for two models of iPhone obtained with different sampling frequency for 15 and 41 parameters, respectively.

TABLE IV
AUTONOMY IN HOURS FOR DIFFERENT SAMPLING FREQUENCY OF ALL 41 PARAMETERS (MEASURED AND CALCULATED)

Frequency (Hz)	41 parameters		15 parameters	
	iPhone 4s	iPhone 5s	iPhone 4s	iPhone 5s
1	5.47 (±1.72)	7.68 (±1.83)	5.10 (±1.90)	7.95 (±1.89)
2	6.37 (±2.20)	10.30 (±2.29)	7.50 (±3.16)	9.47 (±2.38)
3	7.21 (±2.62)	9.16 (±1.86)	6.58 (±2.49)	9.32 (±2.00)
5	5.84 (±2.22)	8.44 (±2.23)	5.95 (±2.32)	8.48 (±2.03)
10	5.26 (±1.72)	7.75 (±1.74)	5.26 (±1.82)	7.80 (±1.78)
20	5.24 (±1.76)	7.59 (±1.87)	5.24 (±1.82)	7.87 (±1.78)
30	5.15 (±1.80)	7.68 (±1.82)	5.23 (±1.78)	7.80 (±1.84)
50	5.09 (±1.81)	7.80 (±1.95)	5.24 (±1.83)	7.47 (±1.74)
100	5.15 (±1.78)	7.65 (±1.77)	5.11 (±1.73)	7.56 (±1.80)

The Analysis Online Service allows to produce report including: (1) Informations about the uploaded file; (2) Results of behavior analysis expressed in duration and as a percentage of total time; (3) A displacement analysis containing the total distance traveled, the number of stop, and stop duration; (4) A speed analysis holding in the average speed, and speed class discretisation. The fig. 5 shows an extract of report produce

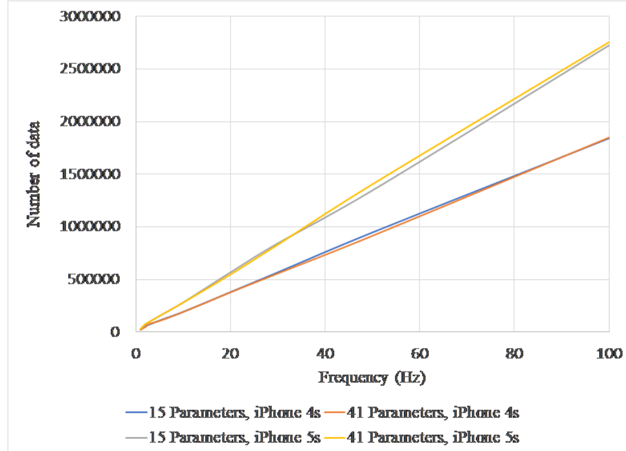
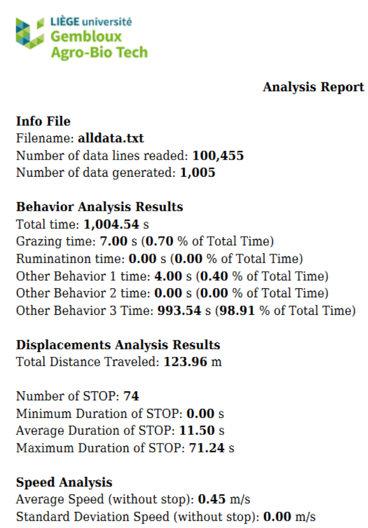


Fig. 4. Performance comparison between iPhone 4s and 5s

from a CSV file logged with Sensor Data.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Analysis Report

Info File
Filename: **alldata.txt**
Number of data lines readed: **100,455**
Number of data generated: **1,005**

Behavior Analysis Results
Total time: **1,004.54** s
Grazing time: **7.00** s (**0.70** % of Total Time)
Ruminatinon time: **0.00** s (**0.00** % of Total Time)
Other Behavior 1 time: **4.00** s (**0.40** % of Total Time)
Other Behavior 2 time: **0.00** s (**0.00** % of Total Time)
Other Behavior 3 Time: **993.54** s (**98.91** % of Total Time)

Displacements Analysis Results
Total Distance Traveled: **123.96** m

Number of STOP: **74**
Minimum Duration of STOP: **0.00** s
Average Duration of STOP: **11.50** s
Maximum Duration of STOP: **71.24** s

Speed Analysis
Average Speed (without stop): **0.45** m/s
Standard Deviation Speed (without stop): **0.00** m/s

Fig. 5. Example of a report produced by the online service

VIII. CONCLUSION

A comparison between two generation of iPhone has been proposed. In terms of precision both iPhone models give the same results on animals. Experimental measures were obtained with table of displacements and checker. The autonomy of iPhone 5s is 50% higher than iPhone 4s. This improvement can notably be explained by the presence of a more efficient co-processor on the iPhone 5s.

The compressibility of data massively acquired can be reduced in mean of 43.5% and this can hardly be improved any further. By opposition, we have shown that individual parameters can be highly compressible. In the future, when the most explicative parameters will be selected for a given research application, the compressibility of data will be improved.

In our future works, we will compare iPhone 4s and 5s with more recent models such as iPhone SE, 6s and 7s. Sensor

Data can be used to collect 41 parameters from the IMU of the iPhone at a frequency up to 100 Hz. However, it is not possible to switch off the screen during the acquisition phase, autonomy of the iPhone using Sensor Data. The use of other software such as Power Sense which operates in the background will undoubtedly significantly increase the acquisition time of the data. This work is necessary for research teams which continue to use recycled refurbished iPhone. Data with 6, 5, 4 and decimals can be explained by the combination of parameters inside groups that limit the possibilities of compression.

The development of Cow Behavior App in Dart with Flutter will be continued especially to introduce data compression without loose of data, and optimized sending of data by micro batch. The Online Analysis Tools will be developed in particular to support other algorithms of behavior analysis, to propose auto-parametrization of algorithm from data and video annoted, and finally to elaborate and train Artificial Intelligence algorithms to automatically extract behavior on the basis of wide amount collected data and their video manually annoted.

ACKNOWLEDGMENT

We would like to thank our colleagues from the CARE AgricultureIsLife (TERRA Teaching and Research Unit, Gembloux Agro-Bio Tech) and the Precision Livestock and Nutrition Axis, without whom this work would not have been possible.

SUPPLEMENTARY MATERIAL

Complete version of results aggregate in the Table 4 and the flutter Mobile App are available on GitHub at https://github.com/Smartappli/cowbehaviorapp.

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